Wavelet Neural Network and Wavenet Performance Evaluation in Hydrodynamic Force Prediction due to Waves on Vertical Cylinders

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Abstract

Neural network and its adaptive wavelets (wavelet networks and wavenets) are used to calculate the wave induced hydrodynamic inline force acting on a vertical cylinder. In order to minimize the error of hydrodynamic force on vertical cylinder members in offshore structures, an offshore structure engineer needs to be able to make reliable prediction of hydrodynamic loads induced by waves. The Wavelet Neural Network (WNN) use wavelets as activation functions of its hidden layer neurons. In WNNs, both the position and dilation of the wavelets are optimized beside the weights, but there are different approaches to construct this kind of networks. In one approach of WNN construction that entitled wavenet, the position and dilation of the wavelets taken to be fixed and only the weights of network are optimized. In this research, wavenet and WNN are employed to predict the inline force time series of a cylinder using wave particle kinematics, namely velocities beside wave surface profile that are gained from experimental data. Numerical results demonstrate that the combination of neural network concept and wavelet theory i.e. wavenet and wavelet neural network provide a more robust tool considering its more appropriate prediction of any new data which the network had not experienced before for predicting the hydrodynamic inline force. Furthermore, WNN has the best results among the other methods.

Keywords

Hydrodynamic; Inline Force; Neural Network; Wavelet; Wavenet

Introduction

Regarding to the increase in power and availability of digital computers, the more extensive use of nowadays theories potential in routine design works by naval architects and engineers has been one of the most important approaches. Most structures in the offshore and coastal regions like platforms, jetties, ocean bridges, seawater intakes and etc. are chiefly composed of tubular elements, whose design is dictated by severe gravity wave forces. Many cylinders failures due to extreme wave forces are reported in the literature. Though, the study of wave forces and moments on these kinds of members has been one of the main research areas and it has attracted the attention of many researchers in the past. In general, the forces on these elements due to sea waves can mainly be divided into two components so called inline force and transverse or lift force. The inline force acts along with wave propagation direction but lift force acts in transverse direction. The data of random waves used in this research were based on the JONSWAP spectrum of $H=1.5\ m$ significant wave height and $T=5.9\ s$ mean period that they are exerted in a cylinder with $0.5\ m$ diameter and the roughness of $k/d = 0.038$. Fig. 1 shows inline and transverse force at a period of time.

Most of the researchers have done a lot of investigations on these kinds of structures. The ultimate objective of such researches is to develop methods of design and construction which help produce structures to be safe, functional, economical and able to resist the forces induced by environment [1,2]. Some of investigations were carried out on hydrodynamic forces acting on the fixed cylinder or oscillating in a still water and several researches have been done on cylinders surging at the same frequency as the incident waves [3-5]. These kinds of forces on offshore structures are usually calculated using different theories such as Morison equation, Froude-Krylov theory, Diffraction theory and so on. Morison have proposed a simple empirical equation to estimate the velocity-dependent drag force and acceleration-dependent inertia force on vertical cylindrical members [6,7]. The hydrodynamic forces on cylinders under the action of waves are usually evaluated using the Morison's equation. Recently,

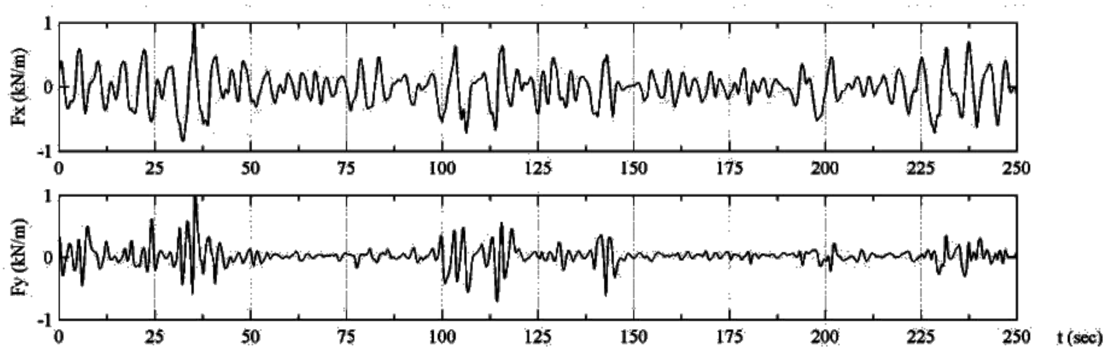

FIGURE 1 INLINE AND TRANSVERSE FORCE SIGNALS NORMALIZED AT A PERIOD OF TIME

developments in soft computing methods such as Artificial Neural Network (ANN), Fuzzy Inference Systems (FISs), Classification and Regression Trees (CART) and Genetic Programming (GP) have rendered them more applicable. Ease of the application, as well as less required computational time, has made these soft computing methods more suitable for wave modeling. Some of investigators [8-15] employed soft computing methods for wave simulation. Jain and Deo presented many applications of ANN in different aspects of ocean engineering [16]. The traditional stochastic time series auto regressive methods have been also used for forecasting purposes, although the auto regressive models are less flexible in fitting to data than ANN models that are self-learning [17]. Deo and Naidu compared the results of forecasting using ANN and auto regressive models [8].

The main objective of this paper is the evaluation of neural network ability and its adaptive wavelets (wavenets) ability in predicting the inline force. The prediction of inline force time series of a cylinder is done using wave particle kinematics, namely velocities beside wave surface profile that are gained from experimental data. Therefore, experimental inline forces are used as output to develop the networks. In the present paper, first a brief review on neural network concept has been presented. After that an introduction to the fundamentals of wavelet theory is explained, consequently neural network adaptive wavelets (wavenets) and designing of a these networks are elaborated. Then the problem is defined in details and finally the simulation results are discussed. Through analysis and comparison of the most appropriate networks output with experimental results it has been found that wavenet approach gives the best quality of fit with available experimental data of hydrodynamic inline force on a vertical cylinder in comparison to neural network and consequently other theories.

Artificial Neural Network

An artificial neural network is a highly simplified model of the biological structures found in a human brain. It is one of the soft computing methods employed widely in the last decade for wave modeling. In this method, every input vector is related with the corresponding output vector [16]. The neural network contains computational elements called nodes or neurons, which undertake the task of combination of inputs and estimation of their weights.

The characteristics of a neural network come from the activation function and connection weights. Since the neural network stores data as patterns in a set of processing elements by adjusting the connection weights, it is possible to realize complex mapping through its characteristics of distributed representations. The most commonly used network and training algorithm combination is the feedforward network with standard back-propagation algorithm [16]. This kind of multi-layer neural network has been applied successfully to solve many difficult and diverse problems [18] by training them with a highly popular learning algorithm known as back-propagation algorithm.

Fundamentals of Wavelet Theory

Wavelet theory is the outcome of multidisciplinary endeavours that brought together mathematicians, physicists, and engineers. This relationship creates a flow of ideas that goes well beyond the construction of new bases or transforms. The term wavelet means a little wave. A function $h \in L^2(R)$ (the set of all square integrable or a finite energy function) is called a wavelet if it has zero average on $(-\infty, +\infty)$ [19]:

$$\int_{-\infty}^{+\infty} h(t)dt = 0 \tag{1}$$

This wavelet must have at least a minimum oscillation and a fast decay to *zero* in both the positive and negative directions of its amplitude. These three properties are the admissibility conditions of a function that is required for the wavelet transform. The wavelet transform is an operation, which transforms a function by integrating it with modified versions of some kernel functions. The kernel function is called the mother wavelet and the modified version is its daughter wavelet. A function $h \in L^2(R)$ is admissible if

$$c_h = \int_{-\infty}^{+\infty} \frac{H(\omega)}{\omega} d\omega < \infty \tag{2}$$

where $H(\omega)$ is the Fourier transform of $h(t)$. The constant C_h is the admissibility constant of the function $h(t)$. The wavelet transform of a function $k \in L^2(R)$ with respect to a given admissible mother wavelet $h(t)$ is defined as

$$w_k(a,b) = \int_{-\infty}^{+\infty} k(t) h^*_{a,b}(t) dt \tag{3}$$

where * denotes the complex conjugate. However, most wavelets are real valued. The daughter wavelets are generated from a single mother wavelet $h(t)$ by dilation and translation as follows:

$$h_{a,b}(t) = \frac{1}{\sqrt{a}} h\left(\frac{t-b}{a}\right) \tag{4}$$

where $a > 0$ is the dilation factor and b the translation factor. The constant term of $1/\sqrt{a}$ is for energy normalization, which keeps the energy of the daughter wavelet equal to the energy of the original mother wavelet [19]. Fig. 2 provides the plots of a mother wavelets (Morlet) accompanied with their daughters that are created using mentioned procedure.

Neural Network Adaptive Wavelet (Wavenet)

The combination of the wavelet transforms theory with the basic concept of neural networks leads to a new mapping network called neural network adaptive wavelets or wavenets is proposed as an alternative to feedforward neural networks for approximating arbitrary nonlinear functions. The wavenet algorithms consist of two processes: the self-construction of networks and the minimization of error. In the first process, the network structures applied for representation are determined by using wavelet analysis. The network gradually recruits hidden units to effectively and sufficiently cover the time-frequency region occupied by a given target. Simultaneously, the network parameters are updated to preserve the network topology and take advantage of the later process. In the second process, the approximations of instantaneous errors are minimized using an adaptation technique based on the LMS algorithms. Each hidden unit has a square window in the time-frequency plane. The optimization rule is only applied to the hidden units where the selected point falls into their windows. Therefore, the learning cost can be reduced [19]. The important steps in training and testing of WNN or wavenet are summarized as follows:

(a) A data set is generated and divided into the training and testing data sets.

(b) The sigmoid activation function of feedforward neurons is substituted with a suitable daughter wavelet.

(c) Appropriate values are assigned to dilation and translation factor of WNN neurons.

(d) The WNN network is trained using training data set.

(e) Performance generality of WNN network is checked using testing data set.

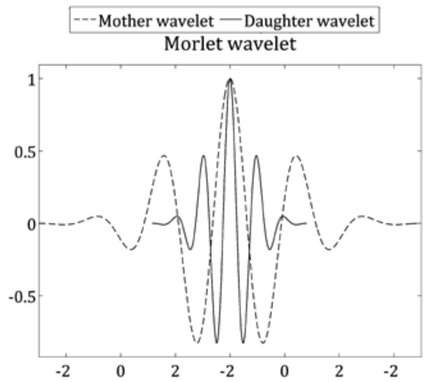

FIGURE 2 MORLET MOTHER AND DAUGHTER WAVELETS

(f) If performance generality is satisfactory, the training process is terminated; otherwise step (g) is performed.

(g) Another value is assigned to dilation factor of WNN neurons.

(h) Steps (d)–(h) are repeated until the proper solution

is met [20].

Wavenet Algorithm

The inversion formula of (5) cannot be expressed directly by finite neural networks (NN), but can be approximately realized using NNs topology with finite hidden units. This is so because most targets are restricted in both the time and frequency domains. The approximated signal of the network $\hat{y}(t)$ can be represented by:

$$\hat{y}(t) = u(t)\sum_{k=1}^{K} w_k h_{a_k,b_k}(t) \tag{5}$$

where K is a number of windowing wavelets, and w_k is the weight coefficients. The neural network parameters w_k , a_k , and b_k can be optimized by minimizing a cost function or the energy function, E, over all time t. Thus by denoting

$$e(t) = y(t) - \hat{y}(t) \tag{6}$$

be a time-varying error function at time t, where $y(t)$ is the desired (target) response. The energy function is defined by

$$E = \frac{1}{2}\sum_{t=1}^{T} e^2(t) \tag{7}$$

To minimize E it can be used the method of steepest descent, which requires the gradients $\frac{\partial E}{\partial w_k}$, $\frac{\partial E}{\partial a_k}$ and $\frac{\partial E}{\partial b_k}$ for updating the incremental changes to each particular parameter w_k, a_k, and b_k respectively. For Morlet mother wavelet, gradients of E are

$$\frac{\partial E}{\partial w_k} = -\sum_{t=1}^{T} e(t)h(\tau)u(t) \tag{8}$$

$$\frac{\partial E}{\partial b_k} = -\sum_{t=1}^{T} e(t)u(t)w_k \frac{\partial h(\tau)}{\partial b_k} \tag{9}$$

$$\frac{\partial E}{\partial a_k} = -\sum_{t=1}^{T} e(t)u(t)w_k \tau \frac{\partial h(\tau)}{\partial b_k} = \tau\frac{\partial E}{\partial b_k} \tag{10}$$

Where $\tau = \frac{t - b_k}{a_k}$. The incremental changes of each coefficient are simply the negative of their gradients,

$$\Delta w = -\frac{\partial E}{\partial w_k}, \Delta a = -\frac{\partial E}{\partial a_k}, \Delta b = -\frac{\partial E}{\partial b_k} \tag{11}$$

thus each coefficient w, b, and a of the network is updated in accordance with the rule

$$w(n+1) = w(n) + \mu_w \Delta w \tag{12}$$

$$b(n+1) = b(n) + \mu_w \Delta b \tag{13}$$

$$a(n+1) = a(n) + \mu_w \Delta a \tag{14}$$

where μ is the fixed learning rate parameter [19].

Results and Discussion

The data used in this research are from the experiments done in delta wave flume of Delft Hydraulics Laboratory (DHL) in Netherlands (LIP Project 10D) [21,22]. The flume is approximately 250 m long, 5 m wide and is normally filled with water to a depth of 5m. The waves were generated by a hydraulically driven plane wave board and their energy is dissipated at the other end of the flume through the use of a sloping concrete beach. The random waves used in the tests were based on the JONSWAP spectrum of H=1.5 m significant wave height and T=5.9 s mean period. The performances of different models were assessed based on calculating the error indices of *Mean Absolute Error* (*MAE*), and the *Root Mean Square Error* (*RMSE*). The coefficients of determination (ϕ^2) and correlation (R) of linear regression between the predicted values from the models and the desired output is also used as a measure of performance. The four statistical of *RMSE, MAE*, ϕ^2 and R parameters formulas that are used to compare the models performances are as follows:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}(t_k - y_k)^2}{N}} \tag{15}$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|t_k - y_k| \tag{16}$$

$$\varphi^2 = 1 - \frac{\sum_{k=1}^{N}(t_k - y_k)^2}{\sum_{k=1}^{N}(t_k - \overline{t_k})^2} \tag{17}$$

$$R=\frac{\sum_{k=1}^{N}(t_k-\overline{t_k})(y_k-\overline{y_k})}{\sqrt{\sum_{k=1}^{N}(t_k-\overline{t_k})^2\sum_{k=1}^{N}(y_k-\overline{y_k})^2}} \quad (18)$$

where t_i and y_i are target and network output for the *i'th* output respectively and $\overline{t_k}$ is the average of target outputs and N is the total number of events considered. The models that minimized the two error measures beside the optimum of ϕ^2 and R are selected as the best one. The whole analysis was repeated several times.

In this study, different algorithms for feed forward neural network were studied in order to select the optimum neural networks and the most proper training algorithm and training function were found to be conjugate gradient and Levenberg Marquardt, respectively. For neural network, the sigmoid and for wavenets, Morlet wavelets were also employed as transfer functions for each network in their hidden layer neurons. MATLAB is utilized for training and testing the networks. The number of hidden layers and their nodes depend on the complexity of the patterns, the network transfer functions and the nature of the problem to be solved. In order to rapid train of the networks and their simplicity, one hidden layer is chosen for all of them. Learning rate and iteration were 0.01 and 400 respectively, while training automatically stopped when the mean square error increased. 70% of data were selected for the training stage and the remaining 30% were used for testing. This division of the data satisfied the statistical similarity required for selecting the training and testing data. Other percentages were also tested and the performances of the models did not change significantly. The training data set is used to train the networks, whereas the testing data set is used to verify the accuracy of the trained neural network and WNN models for the prediction of hydrodynamic inline force. Three important variables selected as input neurons contain wave surface height from still water level, horizontal velocity and vertical velocity. Table 1 shows the range of different input and output parameters for training and testing data sets of the random waves used in these tests. Fig. 3 and Fig. 4 respectively demonstrate fitting error signal and linear regression between predicted signal of recent neural network prediction and experimental data set for training and testing samples.

As activation function of hidden layer neurons in standard feedforward neural networks is a sigmoid function, in order to increase the performance generality of them, activation functions is substituted with Morlet wavelet functions to create its wavenet. The resulted networks are trained by the same method employed for training the feedforward network. With this training method, the values of dilation and translation factors of hidden layer wavelet activation functions were set using trial and error procedure. Equation (10) is Morlet daughter wavelet that was substituted in activation functions of the feedforward neural network hidden layer neurons because of its high performance among other wavelets. A typical topology sample of wavenet is shown in Fig. 5.

$$h(\tau)=\exp(-\frac{\tau^2}{2})\cos(5\tau) \quad (19)$$

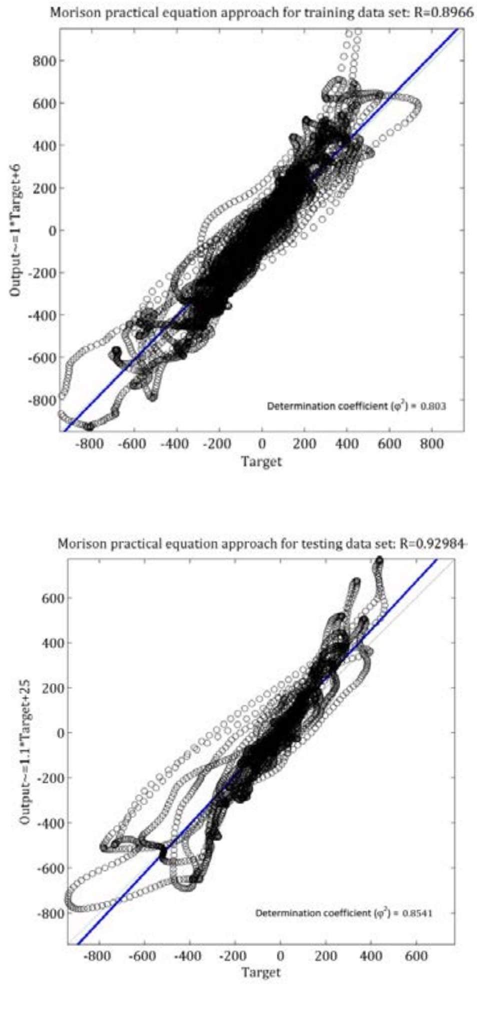

FIGURE 4 LINEAR REGRESSION BETWEEN ANN AND EXPERIMENTAL MEASUREMENTS.

TABLE 1 LIMITS OF USED DATA SET DIVIDED IN TO TWO PARTS, TRAINING AND TESTING SAMPLES

Effective Parameters		**Training data (7000 samples)**			**Testing data (3000 samples)**		
		Min	**Ave**	**Max**	**Min**	**Ave**	**Max**
Input Parameters	H: Wave surface height	-1.0253	-0.0144	1.4577	-0.8569	-0.025	0.9499
	Vx: Horizontal velocity	-1.4688	-0.0689	1.1685	-1.4190	-0.105	0.8889
	Vy: Vertical velocity	-0.7402	0.0071	0.7915	-0.7642	0.0222	0.6738
Output Parameter	Fx: In-line force	-929.46	-22.71	1098.7	-782.67	-26.98	770.341

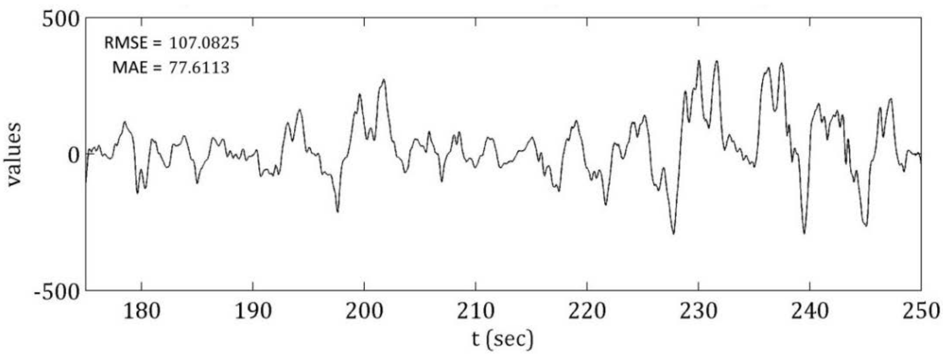

FIGURE 3 FITTING ERROR SIGNAL OF PREDICTIONS ACHIEVED FROM ANN AND EXPERIMENTAL DATA SET

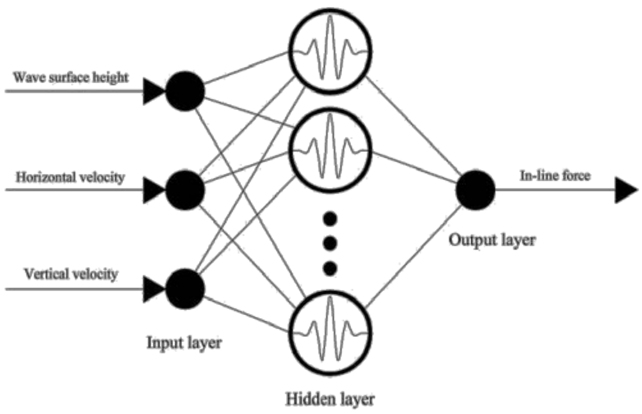

FIGURE 5 A TYPICAL TOPOLOGY SAMPLE OF WAVELET NEURAL NETWORK

Fig. 6 and Fig. 7 respectively demonstrate fitting error signals of predictions achieved from wavenet and experimental data set. Fig. 8 and Fig. 9 also is linear regression between predicted signal of wavenet and experimental data set for training and testing samples. Table 2 contains *RMSE*, *MAE*, determination and correlation coefficients values for neural network, wavenet and wavelet network approaches and subsequently Fig. 10 shows a comparison between the predictions of these procedures with experimental dataset. Figs. 11 and 12 also provide diagrams contain mentioned indices in order to better comparison between the networks efficiencies.

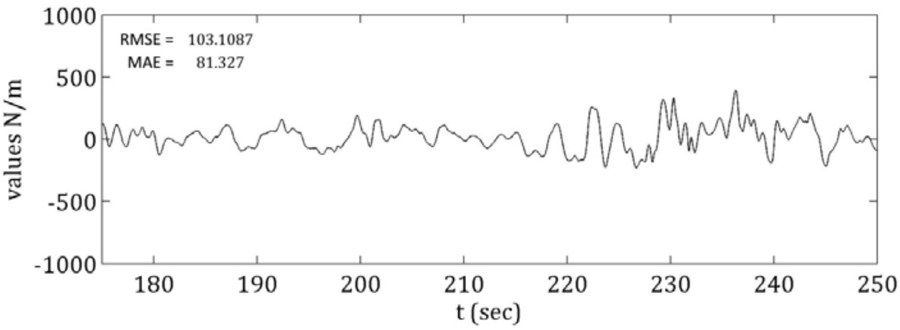

FIGURE 6 FITTING ERROR SIGNAL OF PREDICTIONS ACHIEVED FROM WAVENET AND EXPERIMENTAL DATA SET

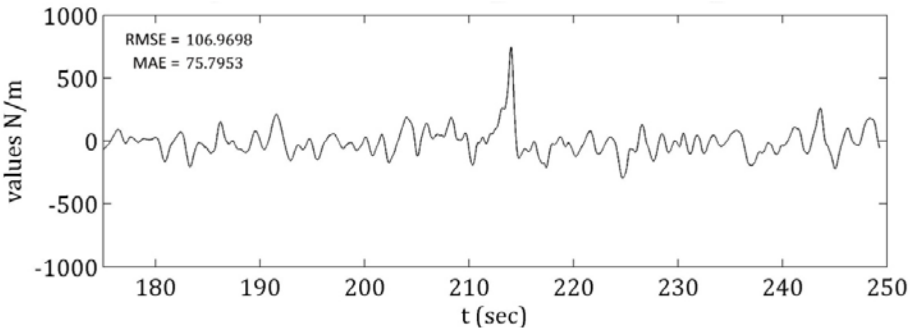

FIGURE 7 FITTING ERROR SIGNAL OF PREDICTIONS ACHIEVED FROM WAVELET NETWORK AND EXPERIMENTAL DATA S

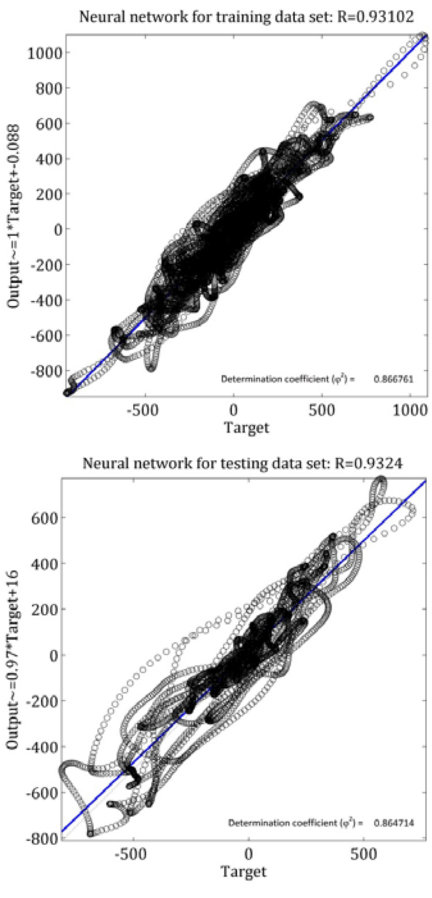

FIGURE 8 LINEAR REGRESSION BETWEEN WAVENET AND EXPERIMENTAL MEASUREMENTS.

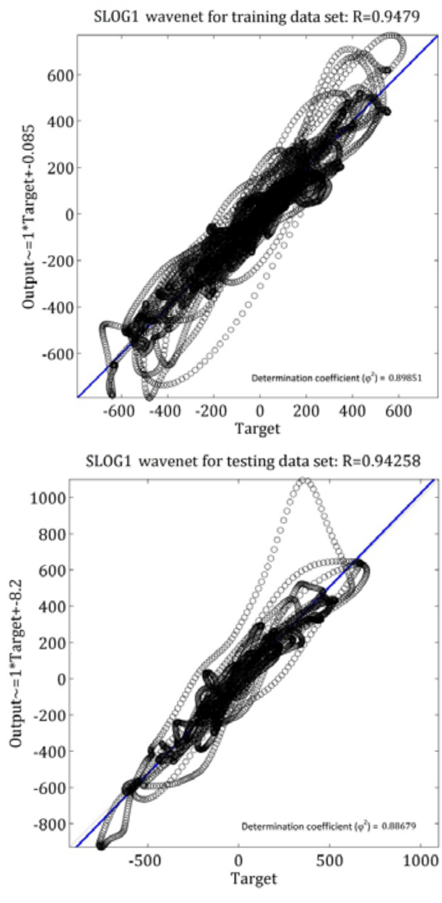

FIGURE 9 LINEAR REGRESSION BETWEEN WAVELET NETWORK AND EXPERIMENTAL MEASUREMENTS

TABLE 2 RMSE, MAE, DETERMINATION AND CORRELATION COEFFICIENTS FOR ANN, WAVENET AND WAVELET NETWORK APPROACHES

Adapted procedure	**RMSE**		**MAE**		**Determination coefficient (ϕ^2)**		**Correlation coefficient (R)**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
ANN	126.6529	107.0825	77.4296	77.6113	0.802995	0.854146	0.8966	0.92984
Wavenet	104.1595	103.1087	82.5697	81.327	0.866761	0.864714	0.93102	0.9324
Wavelet network	85.5046	106.9698	64.195	75.7953	0.898514	0.886799	0.9479	0.94258

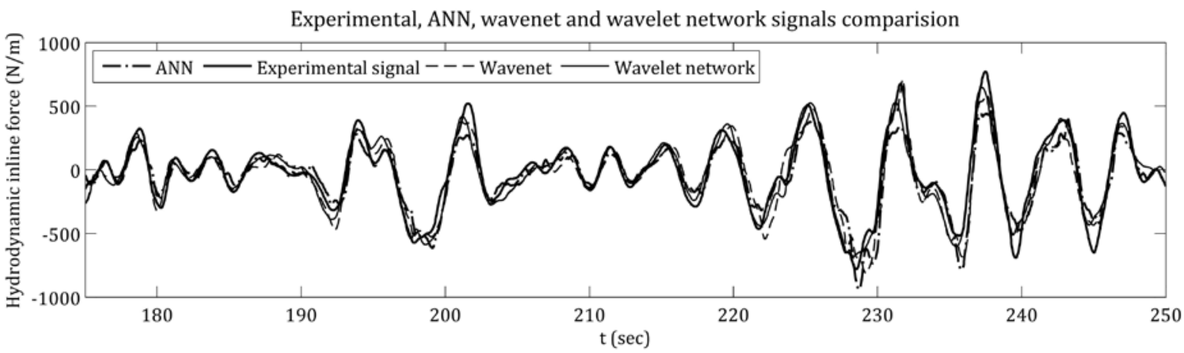

FIGURE 10 ADAPTATION CIRCUMSTANCE BETWEEN PREDICTED SIGNAL OF ANN, WAVENET AND WAVELET NETWORK APPROACHES WITH EXPERIMENTAL DATA SET

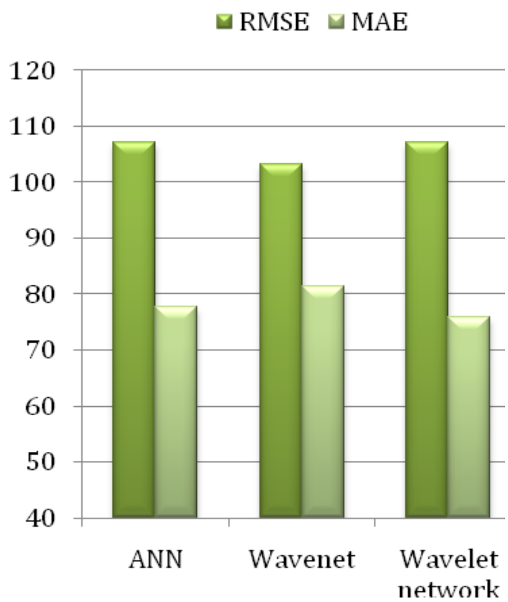

FIGURE 11 RMSE AND MAE ERRORS COMPARISON FOR ANN, WAVENET AND WAVELET NETWORK METHODS FOR TESTING DATA SET

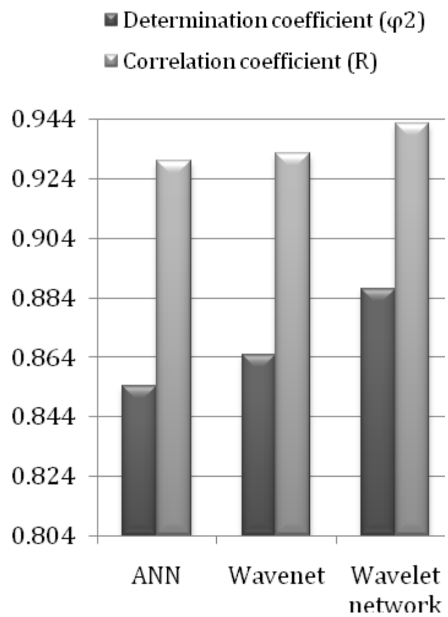

FIGURE 12 DETERMINATION AND CORRELATION COEFFICIENTS COMPARISON OF TESTING DATA SET FOR ANN, WAVENET AND WAVELET NETWORK METHODS

Conclusion

To minimize overall project costs and the risk of damage as a result of designation of vertical cylinders, the engineer who designs the project needs to be able to make reliable predictions of the amount of hydrodynamic inline force. This paper has proposed new methods based on wavelet transform theory and neural network basic concept that called wavenet and WNN as an alternative to feed forward neural network for approximating the hydrodynamic inline force and the potential for applying neural network and its adaptive wavelets has been shown. As it is obvious from the results that artificial intelligence methods can be employed for predicting wave induced hydrodynamic inline force on a vertical cylindrical member in comparison with other computational and time consuming methods since their application is not restricted to the use of coefficients that should be determined experimentally for any environmental condition. Numerical results indicate that substituting different wavelet functions as feedforward neural network transfer functions can enhance the network performance and efficiency. Therefore proposed WNN and wavenet with feedforward neural network structure that uses *Morlet* wavelet function as its hidden layer activation functions is much better in comparison to the standard feedforward in terms of performance generality and furthermore wavelet network can be the best recommendation in estimating the hydrodynamic inline force due to wavelets impressive properties.

References

[1] W. Koterayama and N. Matsumoto, Experimental study of hydrodynamic forces and wave forces exerted on a truss. Ocean engineering, (1982), Vol. 9, No. 3, pp. 221-234.

[2] G. R. Cook and E. Simiu, Hydrodynamic forces on vertical cylinders and the light hill correction. Ocean engineering, (1989), Vol. 16, No. 4, pp. 355-372.

[3] S. K. Chakrabarti and D. C. Cotter, Hydrodynamic coefficients of a mooring tower. Journal of Energy Resource Technol. (1984), 106: 449-458.

[4] S. Nakamura, K. Saito and M. Takagi, On the increased damping of a moored body during low-frequency motions in waves. 5th Int. (1986) OMAE Syrnp., Tokyo.

[5] W. Koterayama and M. Nakamura, Hydrodynamic forces acting on a vertical circular cylinder oscillating with a very low frequency in waves. Ocean engng, (1988), Vol. 15, No. 3, pp 271-287.

[6] J. R. Morison, M. P. O'Brien, J. W. Johnson and S. A. Schaff, The force on a submerged cylinder near a plane boundary. Journal of Transactions of the American Institute of Mining Engineers; (1950), 189, 149–154.

[7] J. R. Morison, J. W. Johnson and M. O'Brien, Experimental studies on wave force on piles. In: Proceedings of the Fourth Conference on Coastal Engineering. ASCE, New York, (1953).

[8] M. C. Deo and C. S. Naidu, Real time wave forecasting using neural networks. Ocean Engineering, (1999), 26: 191–203.

[9] J. D. Agrawal and M. C. Deo, On-line wave prediction. Marine Structures (2002), 15: 57–74.

[10] O. Makarynskyy, Improvingwave predictionswith artificial neural networks. Ocean Engineering (2004), 31: 709–724.

[11] O. Makarynskyy, A. A. Pires-Silva, D. Makarynsky and C. Ventura-Soares, Artificial neural networks in wave predictions at the west coast of Portugal. Computers & Geosciences, (2005), 31: 415–424.

[12] M. H. Kazeminezhad, A. Etemad-Shahidi and S. J. Mousavi, Application of fuzzy inference system in the prediction wave parameters. Ocean Engineering, (2005), 32: 1709-1725.

[13] J. Mahjoobi, A. Etemad-Shahidi and M. H. Kazeminezhad, Hindcasting of wave parameters using different soft computing methods. Applied Ocean Research, (2008), 30: 28-36.

[14] S. Gaur, and M. C. Deo, Real-time wave forecasting using genetic programming. Ocean Engineering, (2008), 35: 1166–1172.

[15] A. Etemad-Shahidi and J. MahjoobiComparison between M5–model tree and neural networks for prediction of significant wave height in Lake Superior. Ocean Engineering, (2009), 36: 1175–1181.

[16] P. Jain, and M. C. Deo, Neural networks in ocean engineering. International J Ships and Offshore Structures, (2006), 1: 25–35.

[17] A. More, and M. C. Deo, Forecasting wind with neural networks. Marine Structures, (2003), 16: 35-49.

[18] N. Kartam, and I. Flood, Artificial Neural Networks for

Civil Engineers: Fundamentals and Applications. ASCE, (1998).

[19] G. Lekutai, Adaptive self-Tuning neuro wavelet network controllers, Blacksburg, Virginia (1997).

[20] S. Gholizadeh, E. Salajegheh and P. Torkzadeh, Structural optimization with frequency constraints by genetic algorithm using wavelet radial basis function neural network. J Sound and Vibration, (2008), pp 312, 316-331.

[21] P. R. Mackwood, Wave and Current Flows around Circular Cylinders at Large Scale. LIP Project 10D, (1993).

[22] J. Wolfram and M. Naghipour, On the estimation of Morison force coefficients and their predictive accuracy for very rough circular cylinders. Applied Ocean Research, (1999), pp 311–328.

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